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Retraction

Retracted: Integration of Artificial Intelligence and Blockchain Technology in Healthcare and Agriculture

Journal of Food Quality

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] S. Vyas, M. Shabaz, P. Pandit, L. R. Parvathy, and I. Ofori, "Integration of Artificial Intelligence and Blockchain Technology in Healthcare and Agriculture," *Journal of Food Quality*, vol. 2022, Article ID 4228448, 11 pages, 2022.

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Research Article

Integration of Artificial Intelligence and Blockchain Technology in Healthcare and Agriculture

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Over the last decade, the healthcare sector has accelerated its digitization and electronic health records (EHRs). As information technology progresses, the notion of intelligent health also gathers popularity. By combining technologies such as the internet of things (IoT) and artificial intelligence (AI), innovative healthcare modifies and enhances traditional medical systems in terms of efficiency, service, and personalization. On the other side, intelligent healthcare systems are incredibly vulnerable to data breaches and other malicious assaults. Recently, blockchain technology has emerged as a potentially transformative option for enhancing data management, access control, and integrity inside healthcare systems. Integrating these advanced approaches in agriculture is critical for managing food supply chains, drug supply chains, quality maintenance, and intelligent prediction. This study reviews the literature, formulates a research topic, and analyzes the applicability of blockchain to the agriculture/food industry and healthcare, with a particular emphasis on AI and IoT. This article summarizes research on the newest blockchain solutions paired with AI technologies for strengthening and inventing new technological standards for the healthcare ecosystems and food industry.

1. Introduction

In the healthcare industry, blockchain and artificial intelligence (AI) technology are unique advancements. Healthcare indices are built using data from Google surveys conducted by several regulating agencies. "Knowledge from Google polls done by plenty of federal regulators is utilized to generate wellness indices." Blockchain technology facilitates the storing of encrypted records required by AI. Healthcare practitioners can use blockchain to view the patient's health records, and AI will use several suggested algorithms, decision-making capabilities, and massive amounts of data. Thus, by incorporating the most recent advancements, the healthcare system will become more service efficient and less costly and democratize healthcare [1]. Additionally, innovative technologies have improved their ability to handle big data sets in real time, enabling faster detection and diagnosis of ailments with automated treatment options and comparisons. Transparency and communication between patients and healthcare professionals are also improved via blockchain technology.

The monitoring of clinical trials can be done using numerical drug design approaches and AI to repurpose commercial pharmaceuticals and explore medication formulation's effectiveness and dose measurement [2]. As a result of this fast-changing atmosphere, governments must determine the most efficient strategies for leveraging resources and accelerate reform while maintaining required

uniformity and compliance. Blockchain technology enables the development and management of content blocks referred to as ledgers and the secure and automated analysis of data [3]. Blockchain aids in the analysis of health data and contributes to its prediction. Research has found that technology aids in a variety of ways, like assessing medical supplies files, encountering computerized learning with pharmacologic cautions, successful implementation of health and treatment regions, and the possibility of reassembling. The captured medical data provides immediate updates to medical specialists, healthcare providers, and payers. This is enhanced further by the collaboration of AI and blockchain. AI enables machines to recognize health trends and patterns. Additionally, the sector of self-driving automobiles has demonstrated their respective capacity to leverage AI to develop driverless vehicles. However, some businesses are developing methods for detecting fraud and determining financial hazards through machine learning. AI plays a factor in predictive value and facilitates the assessment of health info. For example, by contrasting medical supplies files, experiencing automatic teaching with pharmacological alerts, effectual implementation of health and areas of treatment, and the likelihood of reassembling, studies have identified that AI assists in an effective manner. Thus, researchers have used various methodologies based on blockchain and AI techniques to consider the above facts. These techniques allow the healthcare industry to analyze the data at exceptional speeds without compromising accuracy and data security and allowing explicit specialists to get to their information for a fixed period. Hence, the main incentive of this article is to highlight the contributions done by the researchers to provide us with guidance about the role and importance of using AI-Blockchain in EHR systems.

An electronic health record (her) is a repository of medical information produced during clinical settings and incidences. With the expansion of consciousness and home health gadgets, useful info concerning sufferers is now supplied in a timely manner and has lengthy therapeutic value.

The organization of the paper is done in sections to ease the readability. Section 2 presents the application of blockchain and AI in E-health systems and agriculture. Section 3 provides the background study for establishing the concepts. Section 4 provides the literature survey of recent studies followed by Section 5 which sums up the final discussion of the manuscript. The article is lastly concluded in the last section. In this research paper, the complete approach and workflow of the system have been discussed in-depth for the reader to obtain a fundamental notion about the applications of blockchain and AI in the health and food industry.

2. Role of Blockchain and AI in E-Healthcare and Agriculture

This section provides an overview of the applicability of blockchain and AI services in the e-Healthcare and agriculture industry.

2.1. Role in Healthcare. A centralized design, such as the one that underpins a traditional EHR system, entrusts a central institution to monitor, coordinate, and direct the whole network. AI can perform complex computational processes and rapidly evaluate massive amounts of patient data. However, some physicians remain wary about employing AI to impact a patient's wellness, despite AI's tremendous capabilities, which have proved that it can perform numerous dynamic and cognitive processes faster than a human [4, 5]. Figure 1 shows blockchain and AI in healthcare.

Also, a survey carried out in a recent study [6, 7] established that distance displays an inverse association with the consumption of health services. In this era, AI and blockchain are the two technologies that have individually demonstrated their potential growth in the healthcare industry. The field of utilizing these techniques in EHRs data processing has attracted interest from the scientific community. In contrast, blockchain has become more prevalent in the medical domain. It improves the interoperability issues of current EHR frameworks to forestall the altering just as malignant abuse of client's records [8]. Various EHR-based software types, such as Epic, currently use live AI solutions for population health management and clinical decision support systems to predict hospital readmissions, patient risk levels, mortality, and patient deterioration. Likewise, a blockchain-based system called MedRec has provided access to patients. To investigate the above findings, scholars have deployed a range of tactics relying on blockchain and AI approaches. Several capabilities enable the health industry to assess information at high levels while significantly degrading information security or the flexibility for specific expertise to retrieve their info for a set number of hours. As a result, the core objective of this report is to spotlight the expert's contributions in hopes of giving us insight into the position and effectiveness of AI-blockchain in EHR systems [9]. This investigation reviews the effects, proposes a study area, and examines the usage of blockchain in agriculture/food and health, with an emphasis on AI and IoT that has not been incorporated together earlier [10]. Furthermore, new systems have improved their ability to process large data sets in real time, allowing speedier disease identification and diagnosis as well as automated treatment alternatives and comparisons. Blockchain technology also improves transparency and communication between patients and healthcare practitioners.

2.2. Role in Agriculture. IoT, blockchain, and AI-enhanced supply chain provenance solution for the food sector's Industry 4.0. AgrBlockIoT's Agr-Food supply chain management solution integrates IoT devices that generate and consume digital data across the chain. Sensors and other IoT devices monitor agricultural diseases caused by pesticides and product traceability. These sensors transmit data directly to a collection of block-level smart contracts. The smart contract has predefined criteria. Figure 2 provides the distribution of papers pertaining to AI and blockchain in agriculture.

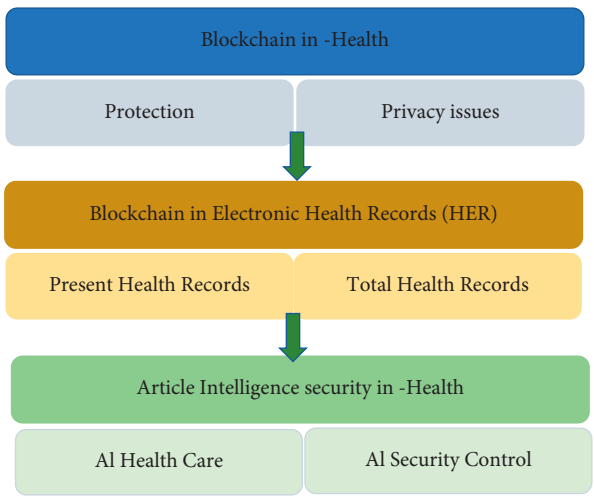

Figure 1: Blockchain and AI in healthcare.

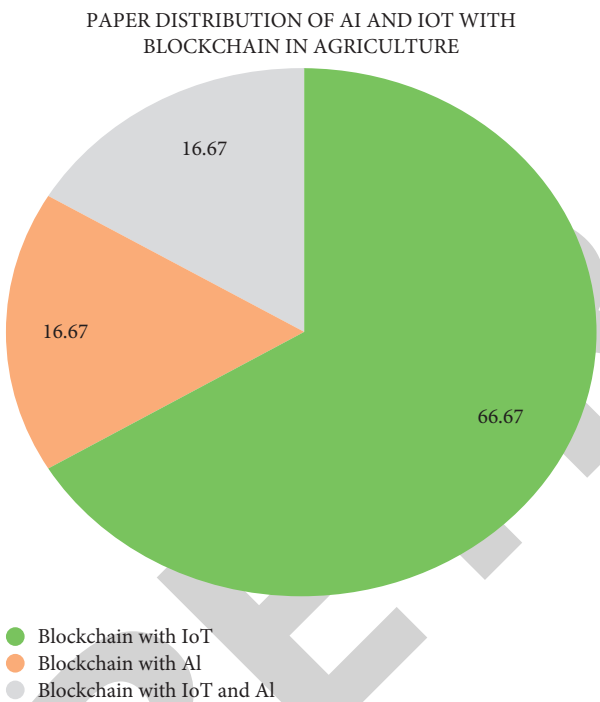

Figure 2: Distributions of papers.

Integration of IoT, AI, and blockchain has the potential to improve the system's efficiency, information traceability, smart farming, and logistics, among other things. In conjunction with IoT devices and machine learning, blockchain technology may give a more comprehensive and valuable image of the agriculture sector. By utilizing IoT, the item/product will be well connected to the resources and goods at each stage of the supply chain. AI is capable of evaluating items. These sensors transmit data directly to a collection of block-level smart contracts.

By utilizing IoT, the item/product will be well connected to the resources and goods at each stage of the supply chain. AI can analyze sowing conditions, crop timing, and agricultural land appropriateness, among other things.

2.2.1. Role of AI Machines in the Agriculture Supply Chain. The employment of machine learning algorithms in the agriculture supply chain's four primary clusters (preproduction, production, processing, and distribution) is gaining traction. Indeed, machine learning technologies are applied at the preproduction stage, most notably for predicting crop yield, soil parameters, and irrigation requirements. Figure 3 provides an overview of blockchain in agriculture.

In the subsequent manufacturing process, machine learning might be utilized to identify diseases and forecast the weather. In the third cluster of the processing phase, machine learning algorithms are used, most notably to predict production planning to achieve high and safe product quality. Machine learning techniques might potentially be used in the distribution cluster, particularly in storage, transportation, and customer analysis. The preproduction cluster is the first link in the chain of agriculture supply. It is primarily concerned with agricultural output forecasting, soil parameters, and irrigation requirements. Numerous studies emphasize the critical nature of agricultural yield production to improve plant management. Indeed, by incorporating input data (equipment requirements, nutrients, and fertilizers) into efficient models powered by machine learning algorithms, these precision agriculture tools aim to assist stakeholders and farmers in making optimal crop yield forecasting decisions and enhancing intelligent farming practices.

3. Background Study

The undeniable accomplishment of Bitcoin popularized blockchain technology to conduct reliable transactions over unreliable networks. A blockchain is a chronologically ordered collection of blocks that include a list of complete and valid transaction records. The block immediately preceding a particular block is referred to as the parent block, while the initial block is the genesis block. A reference (hash value) connects each block to the preceding one, producing a chain.

A health information system is designed to manage, collect, store, and transmit patient's data and the organizational system manages the complete data collected from the hospital repository. After being processed, the data from the information system is sent to three areas, i.e., Patient Management System, Clinical Information System, and Clinical Support Services. It also draws information into an electronic record that clinicians can see at the patient's bedside. On the other side, clinical support system tools suggest the next steps for treatment and alert the information that the patient may not have seen. Figure 4 describes the framework of EHR.

The clinical decision support system is further divided into three types, i.e., the laboratory information system, which is the leading avenue for the laboratory staff to store data and provide laboratory results to healthcare providers. The data collected from Patient Management System is collaborated and stored in the Patient Information Database, which helps to generate the EHR.

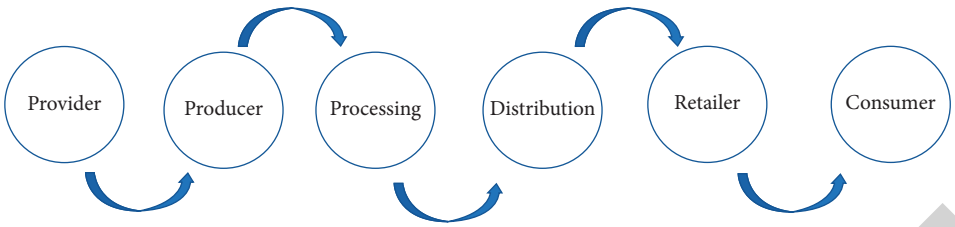

Figure 3: Blockchain in agriculture.

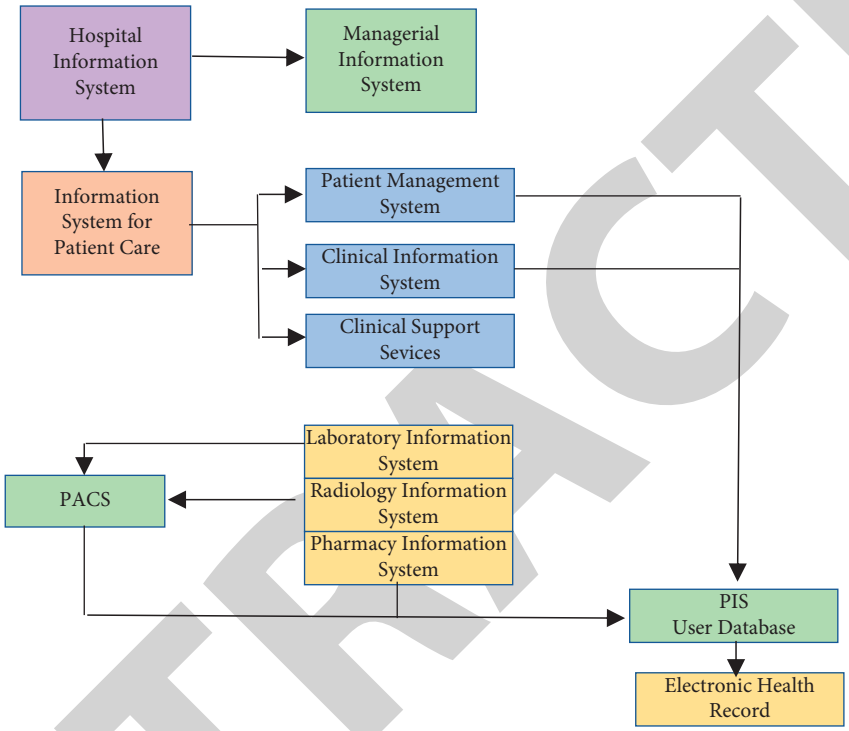

Figure 4: Framework of the EHR [11].

3.1. Types of EHR. There are mainly two types of HER, i.e., cloud-based and client-based HER systems.

(i) Client-based HER: the customer worker-based EHR gives admittance to the destinations through the web. Assume that a rustic center can share and synchronize its clinical records with the emergency clinics and facility through an open EHR worker without much of a stretch. Additionally, put-together clinical staff can log concerning the framework and assist the patients. They may look, sort, and be channel-dependent on specific measures before choosing what cases they should assist with. Figure 5 provides client-server architecture.

(ii) Cloud-based HER: distributed computing introduced in this engineering is a productive segment by which patients and medical laborers can access, store, or recover electronic medical information in the cloud. The equipment and framework programming segments in the cloud are the validation worker, EHR information base, and the middleware, incorporating the organization and the interface. Toward the end, the different medical care places recover the patient's clinical history and record history from the cloud utilizing the framework as assistance and programming as a help. The availability innovation used to associate with the cloud can be wired or remote innovation, for example, 3G/4G, WIFI, and the gadgets utilized are PC. Thus, cloud-based EHR has various advantages for clinical practices. Figure 6 provides a description of cloud-based EHR.

3.2. Functions of EHR. Electronic medical record architecture gives a bunch of fundamental applications that an EHR component must use to improve patient's security, as well as decision support capabilities as documented in Table 1.

4. Literature Survey

It has been utilized to mine EHR information to help in infection finding and the executives, impersonating and enlarging the clinical dynamic of human doctors [18]. The

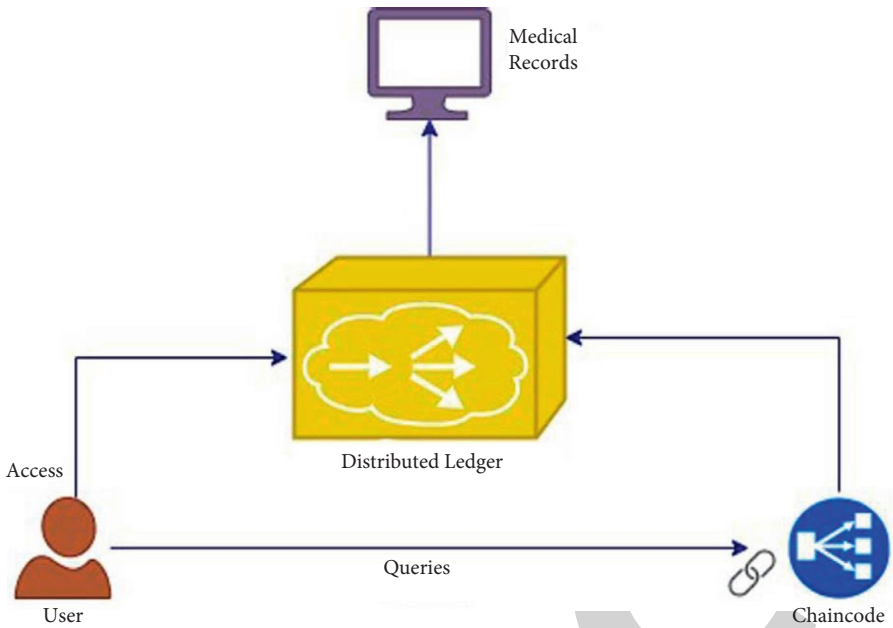

Figure 5: Client-server-based EHR.

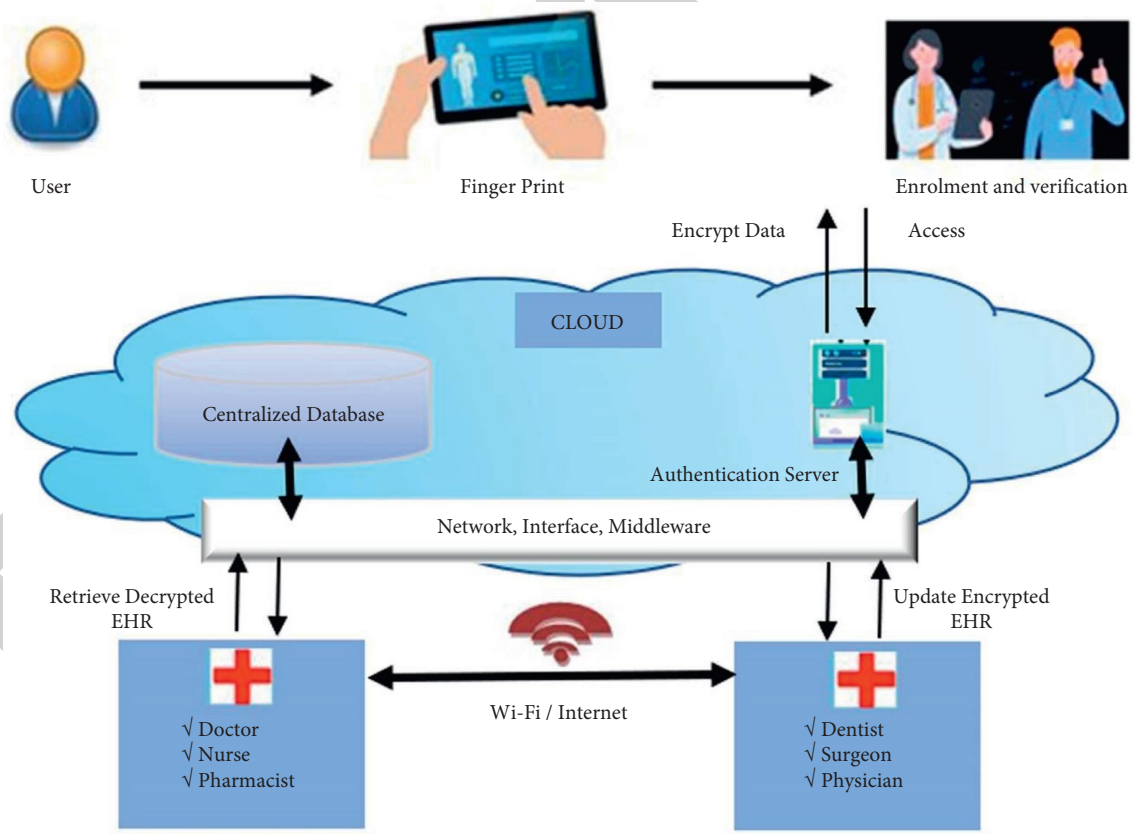

Figure 6: Cloud-based EHR.

application of AI in medicine has two main branches, i.e., virtual and physical; out of these, the virtual branch represents the machine and deep learning. Hence, the work done by the researchers using automated learning in the field of EHR is stated below [19]. Even the recent pandemic situation was accessed using AI-based approaches. The role of AI in EHR is shown in Figure 7.

Wong et al. [20] reviewed AI solutions for dementia care in medical informatics. They looked over and evaluated the present logical systems, identifying the essential concerns

Table 1: Functions of EHR.

Functionalities	Description
Capacity and recovery of medical data and information [12]	Storage refers to the maintenance of information over time, and retrieval can access the information when users need it. Thus, EHR can store and retrieve the patient's information safely and securely.
Results management [13]	It is the ability to take care of the patients to access new and past test results quickly.
Decision support management [14]	It provides timely information to patients and effectively improves patient outcomes that lead to higher quality healthcare.
Electronic communication and connectivity [15]	It refers to the proficient, secure, and promptly available correspondence among suppliers and patients to improve care coherence and decrease the recurrence of unfriendly occasions.
Patient support [7]	This tool allows the patient to admittance to their medical records, gives tolerant instruction material, and permits the patient to act testing to improve the self-administration stable conditions.
Administrative process [16]	It alludes to the highlights, such as planning frameworks, improving proficiency, and offering more assistance to patients.
Reporting and population health [17]	It gives training the capacity to submit information and get vaccination estimates and chronicles from the general wellbeing inoculation data framework.

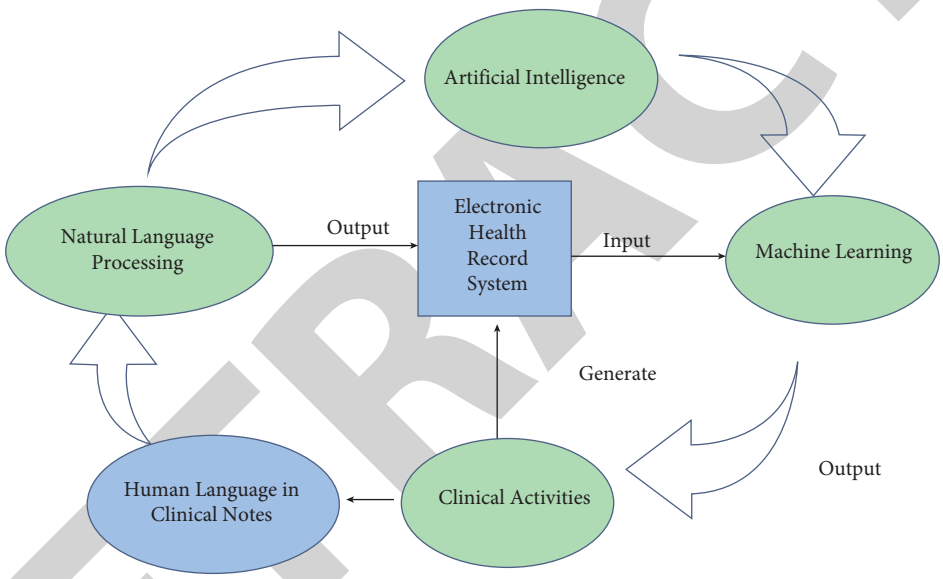

Figure 7: Role of AI in EHR system.

and challenges of having enough medical data. They also illustrated the future possibilities and research implications of severe AI, such as figuring out dementia informatics. Likewise, Marella et al. [21] developed an AI algorithm for deleting exposed adverse effects from EHR notes with free material. They worked on a dataset of 103,564 phrases extracted from the electronic clinical notes of 2695 patients with bosom malignant development. On the other hand, the author looked at four common scenarios that analysts could find helpful in determining when and for what tasks AI could be used to detect medical findings from EHR data. They claimed that medical results based on analytic measurements comprised a variety of clinical components and AI computations that might assist in illustrating the symptomatic complexity.

The authors also testified the enormous promise of computerized medical teaching capabilities and improved medical outcomes for cardiovascular and chronic illnesses patients. Brisimi et al. [22] developed a semiautomated method for screening situations that demonstrated the risks of EHRs from the essential populace-based security disclosing framework. Baxter et al. [23] developed the K-LRT approach and JCC strategy, which identified concealed tolerant groups and modified classifiers for each bunch while validating these computations on massive datasets. Torous and Walker [24] predicted the need for cautious intervention in patients with acute open-point glaucoma using organized data in the electronic health record. Additionally, their technique paved the way for future advancements in automated risk forecasting inside an EHR framework based on core data. Here, Liang [25] studied how innovation might be used to broaden replies to the issues associated with translational examination and clinical consideration.

To ensure security, Jabbar et al. [26] developed a framework to promote character confirmation, simplify the access to and exchange of EHR data, and increase the security of patient information. In the same way, Sun et al. [27] presented a blockchain framework for enhancing data

Table 2: Research analysis.

Authors	Objective of the study	Predicted outcome
Lauritsen et al. [28]	It was developed for the early identification of intense fundamental diseases.	Area under receiver operating curve (AUROC) with mean values: 0.92
Ellis et al. [29]	Classified the patients having a risk of developing dependence, the risk of overdose, etc.	AUROC: 92%
Hong et al. [30]	Developed and evaluated an FHIR-based EHR phenotype framework.	F1- micro: 0.9466
Nori et al. [31]	Worked on the accuracy of a predictive model for dementia.	AUC: 94.4% F1 score: 54.1%
Santos et al. [32]	To improve the quality of patient healthcare.	F-measure: 90%
Lindberg et al. [33]	To utilize tree-based AI techniques to decide indicators of inpatient falls.	AUROC: 0.89 Random forest: 0.90 Boosting: 0.89
Steele et al. [34]	Compared machine learning models and traditional models to identify novel predictive variables.	Net Cox regression model: 95%
Rajkomar et al. [35]	Demonstrated that neural network identified relevant information.	AUROC: 0.90
Wang. et al. [36]	Developed neural network for prediction of the cancer risk.	AUC: 0.922 Sensitivity: 0.837 Specificity: 0.867 PVV value: 0.532
Park and Choi [37]	Demonstrated the deep learning model to assist the clinicians to evaluate infection in patients.	AUROC: 0.97 Average PR: 0.17
Rasmy et al. [38]	To predict the risk of heart failure in diabetic patients and pancreatic cancer.	AUROC: 85.87%
Wang. et al. [39]	Explored the use of features representing patient-level EHR.	Regression: 18.70% Enhanced regression: 9.69%
Meng et al. [40]	Performed bidirectional symbol learning.	PRAUC: 0.76
Gligic et al. [41]	To evaluate the SRML mortality predictor framework and record the parameters of each model.	Accuracy: 81.30% AUC: 81.38%
Omoregbe et al. [42]	Developed the method that worked on named entity identification.	F1- score: 94.6
Priyanga et al. [43]	It is focused on assessing the symptoms of tropical diseases in Nigeria.	Mean SUS: 80.4%
Kavitha and Hanumanthappa [44]	Proposed a novel half and half repetitive neural organization (RNN) vgt6–calculated disarray-based whale streamlining to anticipate the coronary illness.	Accuracy: 99% Specificity: 98% Precision: 96% F-measures: 0.9892 AUC: 98% Prediction time: 9.23 sec
Gupta and Gupta [45]	Their primary goal was to predict cancer from the hybrid algorithm.	Accuracy: 90%
Hamedan et al. [46]	Developed a fuzzy logic-based expert system for the diagnosis and prediction of chronic kidney diseases.	Accuracy: 92.13% Sensitivity: 95.37% Specificity: 88.88% AUC: 0.92 Kappa coefficient: 0.84
Roopa and Harish [47]	Distinguished the area of clots in the guilty party corridor utilizing the data fluffy organization.	Accuracy: 92.30%
Shawwa et al. [48]	Developed to validate the model for predicting acute kidney injury in the ICU using patient data.	AUC of mayo clinic cohort set: 0.690 MIMIC III: 0.656
Shoenbill et al. [49]	To identify the patterns and predictions of lifestyle modification in EHR.	Ensemble model AUROC: 0.831
Hernandez-Boussard et al. [50]	Their goal was to decide if customary RWE guarantees information legitimacy in EHR.	Recall and precision: EHR-S: 51.7% and 98.3% EHR-U: 95.5% and 95.3%
Masino et al. [51]	To build up a model that perceived the baby's sepsis at any rate 4 hours before the clinical acknowledgment.	AUC: 0.85–0.87
Afshar et al. [52]	Their motivation was to prepare and approve an NLP classifier for distinguishing patients with liquor issues.	AUC: 0.78 Sensitivity: 56.0% Specificity: 88.9%
Li et al. [53]	Their purpose was to investigate the utility of an AI approach for patient risk satisfaction.	AUROC: 0.84 Specificity: 93.9% Sensitivity: 63.8% Precision: 90% F score: 73.9%

Table 2: Continued.

Authors	Objective of the study	Predicted outcome
Hung et al. [54]	Their aim was to apply a deep neural network to achieve high modeling power.	AUC: 0.920 Sensitivity: 92.5% Specificity: 79.8%
Samad et al. [55]	They used AI to more precisely anticipate endurance after echocardiography.	Accuracy: 96% AUC: 0.82
Li et al. [56]	They intended to explore the viability of BERT-based models for biomedical.	F1 score: 93.82%

interoperability and integrity in the context of EHR sharing, allowing for the trade of EHRs between multiple clinical suppliers and a decentralized Trusted Third-Party Auditor to ensure data respectability. This devised a property-based encryption scheme for the safe storage and efficient exchange of electronic clinical data in an interplanetary file system stockpiling environment. It regulated the entry of electronic healthcare data without interfering with constructive recuperation. Table 2 provides the research analysis.

5. Discussion

Rapid advancements in healthcare digitization have resulted in massive electronic patient records. This advancement paves the way for never-before-seen standards for protecting healthcare data and for the use and transmission of these records. E-Health structures may be a more viable option for preserving medical records on a global and linked scale and allowing for more access to clinical information based on the system's requirements. There is a significant growth in the number of candidates for EHR in E-Health, which utilizes mobile devices to deliver medical support. Some medical services include data collection online and in-person and data sharing with other medical service providers. The EHR is a digital-based platform for storing and processing medical data readily available to patients and physicians. The primary goal of an EHR is to monitor and retain patients' medical data better securely. This covers the patient's entire medical history, current health status, and demographic information about the patient. To ensure consistency, service providers must update the provided services. Indeed, prior studies [57] advocated a variety of policies and norms to safeguard EHR privacy. These guidelines and regulations impose stringent security requirements to share and exchange health data. If sharing did not adhere to the guidelines, severe sanctions were levied on violators. The incorporation of AI and multiagent-based systems into health data facilitates management decision-making and action and communication and coordination. The primary objective of this system is to provide methodologies, tools, and infrastructure for managing and transmitting health data via the EHR. Electronic Health Records are real-time and patient-centric solutions. This enables authorized individuals to view and manage patient data. These data are in a digital format and are gathered following previously established criteria for storing patient health information. The data in this EHR can be accessed by the patient, an authorized physician, or a service provider. It is kept on cloud-based servers that are only accessible to authorized users. A network was used to connect the users and the data. The network handled all requests and transmissions. While this EHR has several advantages, it is more susceptible to many forms of threats. This is due to the way it was designed. Numerous dangers to data collection were discovered in these EHRs. As a result of these dangers, some users are hesitant to utilize this EHR to store and transfer their health data. As a result, this is proposed as a unique technique for guaranteeing privacy and security by merging AI agents and blockchain. In the health industry, blockchain enables clients to have complete visibility and transparency of the commodities. There are also a few electronic health record software vendors, which are listed as follows:

(i) EPIC: Epic spotlights huge clinical meetings and inpatient settings. KLAS has positioned Epic's EHR as the best in KLAS for a very long time in the most significant section. It is worker obsessed and designer driven with a product that is anything but difficult to exploit and execute in the association [58, 59].

(ii) CERNER: Cerner is now the primary provider of Health IT arrangements and is the biggest supplier of frameworks for inpatient care. It upholds 55 or more specialties besides the medical sector, monetary, and vast links [60].

(iii) CARECLOUD: Care-Cloud offers to fund the successful EHR, train the executives, and persistence skills in the board indoctrination [61]. KLAS has taken Care-Cloud as a primary supplier of cloud-based income cycle of the executive administrator for the concern of mobile rehearses.

(iv) ATENAHEALTH: Atenahealth provides a cloud-based income sequence pact outfitted for the large, interdisciplinary doctor meetings. It provides tuition to the higher officials and EHR arrangement and an advanced UI alongside the cloud-based capacities like access from any program.

(v) NEXTGEN: NextGen controls more than 155,000 doctors through their EHR programming. It is an entirely claimed auxiliary of Quality Systems, Inc. NextGen tailors its product to the necessities of wandering practices and holds a more grounded

position with slight to medium practices. Its contribution is principally customer workers with an abundance of clinical substance for certain specialties.

Blockchain technology may be used to monitor the expertise of medical experts, allowing trustworthy medical institutions and healthcare organizations to document the credentials of their employees, therefore assisting healthcare organizations in streamlining their employment process. ProCredEx, located in the United States, has created a medical credential verification system based on the R3 Corda blockchain technology.

6. Conclusion

Healthcare providers, patients, and other stakeholders have used electronic storage of medical prescriptions and other pertinent records. These reports include sensitive patient information. As a result, there is a requirement to store this information decentralized for providing data and identity security. Numerous individuals see doctors regularly and receive various prescriptions and evaluations. Healthcare data is required in case of an emergency. Blockchain-based architectures can be used for storing and processing medical data (handwritten medications, printed pills, and printed messages) utilizing various AI techniques such as optical character recognition (OCR) to create a single patient medical history report. The optical mark recognition technique is an enterprise option for information extraction from the textual content text in a document image or electronic document and transfers the content into a robot framework for data manipulation such as altering or finding. For ease of use and reading, the report displays just the most critical information and is safely saved on a decentralized blockchain network for further use. This research examined cutting-edge blockchain research in healthcare and proposed the integration of AI and a blockchain-based approach to healthcare administration. Multiple studies have established the significance of machine learning deep learning and ensemble learning models as efficient prediction models in healthcare. Numerous projects in various nations and economies demonstrate that governments and relevant corporate sectors are increasing their involvement in digitizing healthcare systems. In this paper, the complete approach and workflow of the system have been discussed in-depth for the reader to obtain a fundamental notion about applications of blockchain and AI in the health and food industry. In the future trends. AI could be utilized to identify and prioritize certain sufferers for dosage surveillance, which is vital for prescribed drug manufacture and may limit turnaround times.

Data Availability

The data shall be made available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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